

RESEARCH ARTICLE

Hierarchical cluster-tendency analysis of the group structure in the foreign exchange market

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A hierarchical cluster-tendency (HCT) method in analyzing the group structure of networks of the global foreign exchange (FX) market is proposed by combining the advantages of both the minimal spanning tree (MST) and the hierarchical tree (HT). Fifty currencies of the top 50 World GDP in 2010 according to World Bank's database are chosen as the underlying system. By using the HCT method, all nodes in the FX market network can be “colored” and distinguished. We reveal that the FX networks can be divided into two groups, i.e., the Asia-Pacific group and the Pan-European group. The results given by the hierarchical cluster-tendency method agree well with the formerly observed geographical aggregation behavior in the FX market. Moreover, an oil-resource aggregation phenomenon is discovered by using our method. We find that gold could be a better numeraire for the weekly-frequency FX data.

Keywords foreign-exchange market, hierarchical cluster-tendency method, hierarchical tree, minimum spanning tree

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1 Introduction

Much attention has been paid to the studies of econosystems in recent years. In financial markets, the topology network analysis is a widely used technical tool and provides efficient methods to describe their structural and market properties. Mantegna [1] first proposed topology network analysis in terms of the technical tool of minimal spanning tree (MST) to analyze the similarities among stock prices and found significant implications for portfolio optimization. In recent years, the network-based approach has been widely used to explore market properties in financial markets, such as equity markets [2, 3] and the stock markets of Korea [4–6], Athens [7], Europe [8], NYSE [9–13], Brazil [14], and so on. As powerful tools, the minimal spanning tree (MST) and the hierarchical tree (HT) have been widely applied to the analysis of financial markets, especially the stock market [15–21]. The MST and HT methods have also been applied to stud-

ies of the foreign exchange (FX) market [22–29], and a number of behaviors have been revealed.

The FX market is the largest financial market that performs daily transactions with trillions of US dollars. The currency of a country is very important, and it reflects the overall economic status of a country. The foreign exchange rate is thought to be a measure of economic balance between different countries. It is important to investigate the interaction of currencies to empirically establish the relations between microscopic market fluctuations and macroscopic economic states. Geographical aggregation was discovered in the FX market [27], as well as industrial aggregation in stock market [1]. USD and EUR are confirmed to be predominant currencies [28], and their behaviors have been extensively discussed [26]. The evolution of the FX market is a manifestation of the global economic status, and this interesting issue has also been studied, especially that before and after different economic crises [26–29].

The MST and HT provide a useful guide for determin-

ing underlying economic or regional causal connections in individual currencies. They also show the interconnection among currencies, detecting clusters and taxonomic relations in foreign exchange markets. These trees, introduced by Mantegna [1], and Mantegna and Stanley [30], have been applied to analyze currency markets, especially to find clustered structure of currencies and the key currency in each cluster and to resolve contagion in a currency crisis [26–29].

However, the understandings of the MST and the HT are still not enough in studies of various economic networks. Although the hierarchical structure is given by the HT, the deeper meaning and the relation between the HT and the MST are not completely clear. The MST may reveal the strongest correlations of each currency but fails to exhibit the cluster information of the networks, while HT just opposites [28]. In this paper we suggest a method called the hierarchical cluster-tendency (HCT) analysis to expand the understanding of the FX market by combining the advantages of the HT and the MST. We further exhibit the effectiveness of the method by analyzing the global foreign exchange market in 2012.

In the analysis of the 2012 FX market, we use NZD (New Zealand dollar) and gold as two numeraire. Many researches pointed out that gold should be rejected due to the high volatility [26, 27]. However, these studies only focus on the daily or higher-frequency data. Here we are interested in the relationship between the currency numeraire and the metal numeraire, and try to find if there is a mutual steady currencies situation. So weekly data is adopted, for monthly data is often used to study a long-term situation during decades [31, 32], and daily data may introduce high volatility.

The paper is arranged as follows. In Section 2, we give an introduction to the hierarchical cluster-tendency method. To introduce this approach, we first review the well-known Pearson correlation coefficient, the MST, and the HT. Section 3 gives the data we are going to analyze, i.e., the top-50-currency system of the 2012 FX market, by using our HCT approach. In Section 4, we propose an analysis of the 2012 global FX market by presenting the colored HT and MST, where clustered structures are found and discussed. Section 5 gives the conclusion of our studies.

2 The hierarchical cluster-tendency approach

In the analysis of economic time series, a central quantity in revealing the economic dynamics information embedded in complicated data is the correlation coefficient, and all other further statistical analysis are based on this quantity. Here we briefly introduce respectively the correlation coefficient, the minimal spanning tree (MST)

and the hierarchical tree (HT), which are used to contracture hierarchical taxonomy of the global FX markets. We further introduce our method called the hierarchical cluster-tendency (HCT) analysis.

2.1 The correlation coefficient

The logarithmic return of the exchange rate P_i is defined as [1, 26–28]

$$R_i = \ln P_i(t) - \ln P_i(t - \tau) \quad (1)$$

where i is the numerical labels of an exchange rate time series and $P_i(t)$ is the i th exchange rate at time t , while τ is a time interval in discretizing the time series. Here we take the interval as one week (seven days) to keep the consistency for both the NZD and XAU numeraire. Although high-frequency data (e.g., hourly and daily data) may provide us more valuable information about the FX market, we found that weekly data is enough to reveal some very interesting behaviors of the foreign exchange dynamics.

The correlation coefficient between the logarithmic returns of the i th and the j th exchange rates is given as [1, 24–26]

$$C_{ij} = \frac{\langle R_i R_j \rangle - \langle R_i \rangle \langle R_j \rangle}{\sqrt{(\langle R_i^2 \rangle - \langle R_i \rangle^2)(\langle R_j^2 \rangle - \langle R_j \rangle^2)}} \quad (2)$$

and $\langle \rangle$ is the statistical average of the time series over all the trading time. Statistically the range of C_{ij} is from -1 to $+1$. The minimum value -1 means that two currencies are completely anti-correlated and the maximum $+1$ implies a complete correlation between R_i and R_j , while $C_{ij} = 0$ means an uncorrelated relation. Obviously, $C_{ii} = 1$, implying the auto-correlation.

Since we have N time series, each pair of series give rise to a correlation coefficient, then all the coefficients C_{ij} form a symmetric $N \times N$ matrix $\{C_{ij}\}$. Furthermore, a distance matrix $\{d_{ij}\}$ can be calculated by introducing the distance between two currencies as [1, 24–26]

$$d_{ij} = \sqrt{2(1 - C_{ij})} \quad (3)$$

The definition of the distance d_{ij} should fulfill the following three axioms of Euclidean distance [1, 25]:

- (i) $d_{ij} = 0$ if and only if $i = j$
- (ii) $d_{ij} = d_{ji}$
- (iii) $d_{ij} \leq d_{ik} + d_{kj}$

Hence $\{d_{ij}\}$ forms a distance matrix corresponding to the correlation matrix.

2.2 The minimal spanning tree (MST)

The MST is a fully connected graph with a minimal num-

ber of links and without isolated nodes. It is generated by the distance matrix and then reduces the information from $N(N-1)/2$ separated correlation coefficients to $(N-1)$ links. All these links can be used as the edges of a tree, as well as N time series can be seen as nodes, thus they build up a weighted graph [25].

Generally, there are different algorithms to generate the MST. Here we adopt the Prim's algorithm [37]. The steps for this algorithm are as follows:

- (1) Find an arbitrary node in the network, add it and its edge with the minimum weight into the MST;
- (2) In the rest part of network, look for another node with the minimum weight edge to the MST, add it and that edge.
- (3) Repeat steps (1) and (2) until the MST with $(N-1)$ links is finished.

2.3 The hierarchical tree

The concept of ultrametricity is introduced during the construction of the HT. Such ultrametricity or ultrametric distance has been introduced decades ago [36]. The ultrametric distance between two objects i and j , or the maximal d^{ij} , is encountered when moving from i to j over the shortest part of the MST connecting i and j . Comparing with the Euclidean distance, d^{ij} shows a stronger condition than $d^{ij} \leq d_{ik} + d_{kj}$, that is $d^{ij} \geq \max(d_{ik}, d_{kj})$, thus the d^{ij} is a subdominant ultrametric distance [27], which is used to construct the HT.

As well as the MST, HT has also been widely used in the analysis of the FX markets [1, 24–26].

2.4 Hierarchical cluster-tendency (HCT) analysis

By analyzing the HT and MST, we are facing the situation of revealing the clustering property of the FX network. In traditional pictures given by the HT and MST, the clusters presented by the network are often misleading. Two seemingly nodes in one cluster often does not belong to this cluster. Moreover, neither HT nor MST gives the affiliation or tendency information of some leaf nodes in the network. Therefore, a challenging task arises, i.e., we wish to distinguish the affiliations (the “color”) of every element by coloring and further classifying them. To do this, we introduce the HCT method and explain how it works. The HCT method intends to reveal the affiliation property of elements in a network. The main process of our work is: i) construct the MST on the basis of a distance matrix, ii) apply the HCT method in the process of drawing the “colored” HT, iii) draw the MST and color the nodes by using the HCT results. Here we give an example to explain our HCT

approach in more detail and how it works.

We use the following artificial MST distanced linking set containing 8 elements labeled by $\{a, b, c, d, e, f, g, h\}$, as shown in Fig. 2(a). The first seven shortest distances defined by Eq. (3) are given as: $d(a, b) = 0.05$, $d(a, c) = 0.12$, $d(e, d) = 0.03$, $d(f, e) = 0.15$, $d(e, c) = 0.21$, $d(g, b) = 0.32$, $d(h, f) = 0.45$. We first construct the HT and the respective MST by using the above information. Different from the previous constructing schemes, we apply the “coloring” technique during the construction process of the HT and the MST.

First, we build the HT by the following steps:

- (1) Connect nodes a and b by red lines in the coordinates on the vertical axis 0.05.
- (2) Connect c to the midpoint of the linkage between a and b by red lines on the vertical axis 0.12.
- (3) Repeat similar steps as (1), (2) to $e-d$ and $f-e$ by using blue lines because these nodes form another cluster, then two individual clusters appear. We call the cluster marked as red cluster A (containing elements a, b , and c). The cluster marked as blue is called B (containing elements d, e , and f), as shown in Fig. 1(a).
- (4) Since e connects to c on the vertical axis 0.21, connect the midpoint of two clusters' top, then two clusters are connected. Obviously, A and B form a bigger cluster called C, thus A and B are C's sub-clusters while g and h are two out-of-C nodes, as shown in Fig. 1(b).
- (5) Node g connects to b on the vertical axis 0.32. Because g connects into C by connecting b in A, then node g is A-tendentious. Thus g is in A's sphere of influence, and marked as pink, as shown in Fig. 1(c).
- (6) Node h connects to f on the vertical axis 0.45. Because f is a node in B, then node h is B-tendentious. Thus f is in B's sphere of influence, marked as light-blue, as shown in Fig. 1(d).

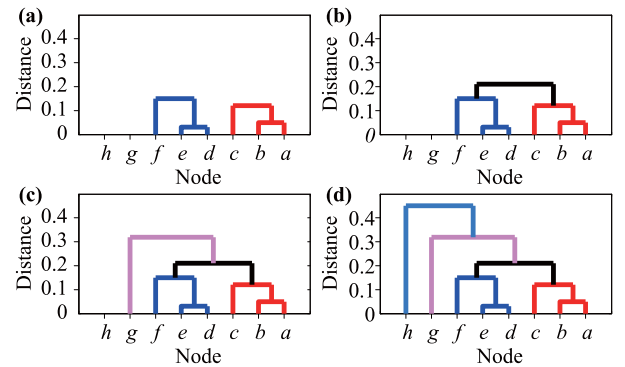


Fig. 1 (a) HT after step (3), two cluster A (red) and B (blue) appear; (b) HT after step (4), a larger cluster appears and contains two sub-clusters, (c) HT after step (5), an A-tendentious node (pink) connects to the tree, (d) HT after step (6), a B-tendentious node (light-blue) connects to the tree

Although g and f are all out-of-C nodes and connect

to C finally, they choose the different paths in connecting different sub-clusters in C . Thus they are in different spheres of influence. Now we can see that the process of constructing the HT is important to hierarchical cluster-tendency analysis.

The HCT can be theoretically understood as follows: During the construction of the MST by using distance matrix, more and more edges are added into the graph set. In the given example above, after the adjunction of edge (e, c) , we will look for the next edge. According to the Prim's algorithm, the distance of the next edge (ζ, η) , $d_{\zeta\eta}$, should satisfy

$$d_{\zeta\eta} = \min(\{d_{\alpha\beta}\}), \quad \alpha \in \{g, h\}, \quad \beta \in \{a, b, c, d, e, f\}$$

Since we know that $\mathbf{A} = \{a, b, c\}$, $\mathbf{B} = \{d, e, f\}$, and $\mathbf{C} = \{\mathbf{A}, \mathbf{B}\}$, we can rewrite the relation above as:

$$d_{\zeta\eta} = \min(\{d_{\alpha\beta}\}), \quad \alpha \in \overline{\mathbf{C}}, \quad \beta \in \mathbf{C}$$

that is

$$\begin{aligned} d_{\zeta\eta} &= \min(\{\{d_{\alpha\mu}\}, \{d_{\alpha\nu}\}\}) \\ &= \min(\min(\{d_{\alpha\mu}\}), \min(\{d_{\alpha\nu}\})), \\ \alpha &\in \overline{\mathbf{C}}, \quad \mu \in \mathbf{A}, \quad \nu \in \mathbf{B}. \end{aligned}$$

Then we find

$$d_{\zeta\eta} = \min(d_{gb}, \min(\{d_{\alpha\nu}\})), \quad \alpha \in \overline{\mathbf{C}}, \quad \nu \in \mathbf{B}$$

and $d_{\zeta\eta} = d_{gb}$, and the respective edge (g, b) .

$\mathbf{A}$ and $\mathbf{B}$ are not defined arbitrarily, they are the two individual clusters in the HT. Thus, we can see that, by introducing the result of HT, the connection between g and b has a special meaning: the strongest relationship between the remaining part $\overline{\mathbf{C}}$ and the existed hierarchical structure is a connection between g and $\mathbf{A}$, that is,

g is an external extension of $\mathbf{A}$, or, g is in $\mathbf{A}$'s sphere, which is called as HCT.

According to the taxonomies classified above, we can further color the nodes in the MST. In Fig. 2(a), the uncolored MST is given. In Fig. 2(b), we present the colored MST according to the above steps. We can see that clusters are not obvious in the traditional uncolored MST, while we can clearly recognize the clusters and their sphere of influence by coloring the nodes in Fig. 2(a). Furthermore, such a core cluster and its respective sphere form a new large group as a meaningful complement to the ultrametric structure.

Furthermore, a specific node which connects with many other nodes naturally forms a center. Thus this node would be an important node in a respective MST, that is, a hub. Generally, the node that connects to this hub should be in either the cluster or the sphere of influence of the hub (except for crossing cluster connection, such as the black one in Fig. 1).

3 Data

Our following analysis is based on the data of the FX market by focusing on top 50 currencies. The currencies are selected from the Top50s of World 2010 GDP according to World Bank's database [19]. Between each pair of currencies, there is a weekly exchange rate time series, thus there are $50 \times (50 - 1) = 2450$ time series. Each rate time series contains 52 data for the year 2012. All weekly exchange rates are obtained from Oanda website's open weekly historical-rates [20].

In this work, we choose NZD as the currency numeraire and XAU (gold price per oz) as the metal numeraire. The

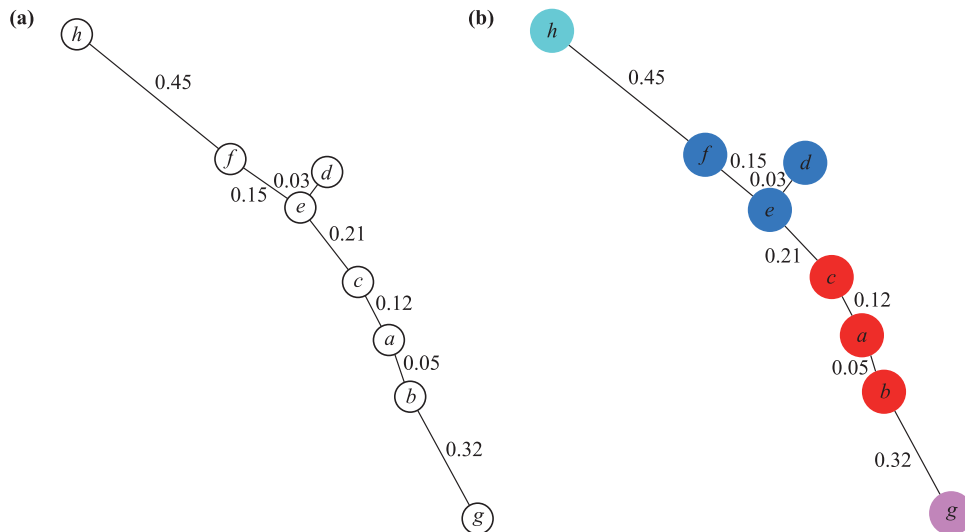


Fig. 2 Distanced MSTs: (a) The uncolored, (b) The colored. Cluster A's nodes are red, and the respective sphere node is pink. Cluster B's nodes are blue, and the respective sphere node is light-blue.

NZD is selected as the numeraire because it is an appropriate minor currency. The numeraire will be excluded from the results, thus the absence of a major currency will affect the pattern of network clustering [27, 28, 35]. Since no major currencies are absent in the XAU-based network, we keep them from being the numeraire and choose a minor one instead. NZD is such a minor currency that can be excluded from the result [35]. All currencies and their symbols are presented in Table 1.

4 The FX market in 2012: An HCT analysis

4.1 The NZD-based FX network analysis

In this section, we study the MSTs and HTs of the global FX market in 2012 in terms of the HCT method. By using the exchange data of the 50 currencies presented in Table 1, we give the NZD-based results in Fig. 3, where the HT and MST are worked out respectively by Fig. 3(a) and (b). Different from the traditional HT result, here we present a colored HT by using the HCT method. The coloring scheme clearly reveals the clustering property of the 50 dominant currencies.

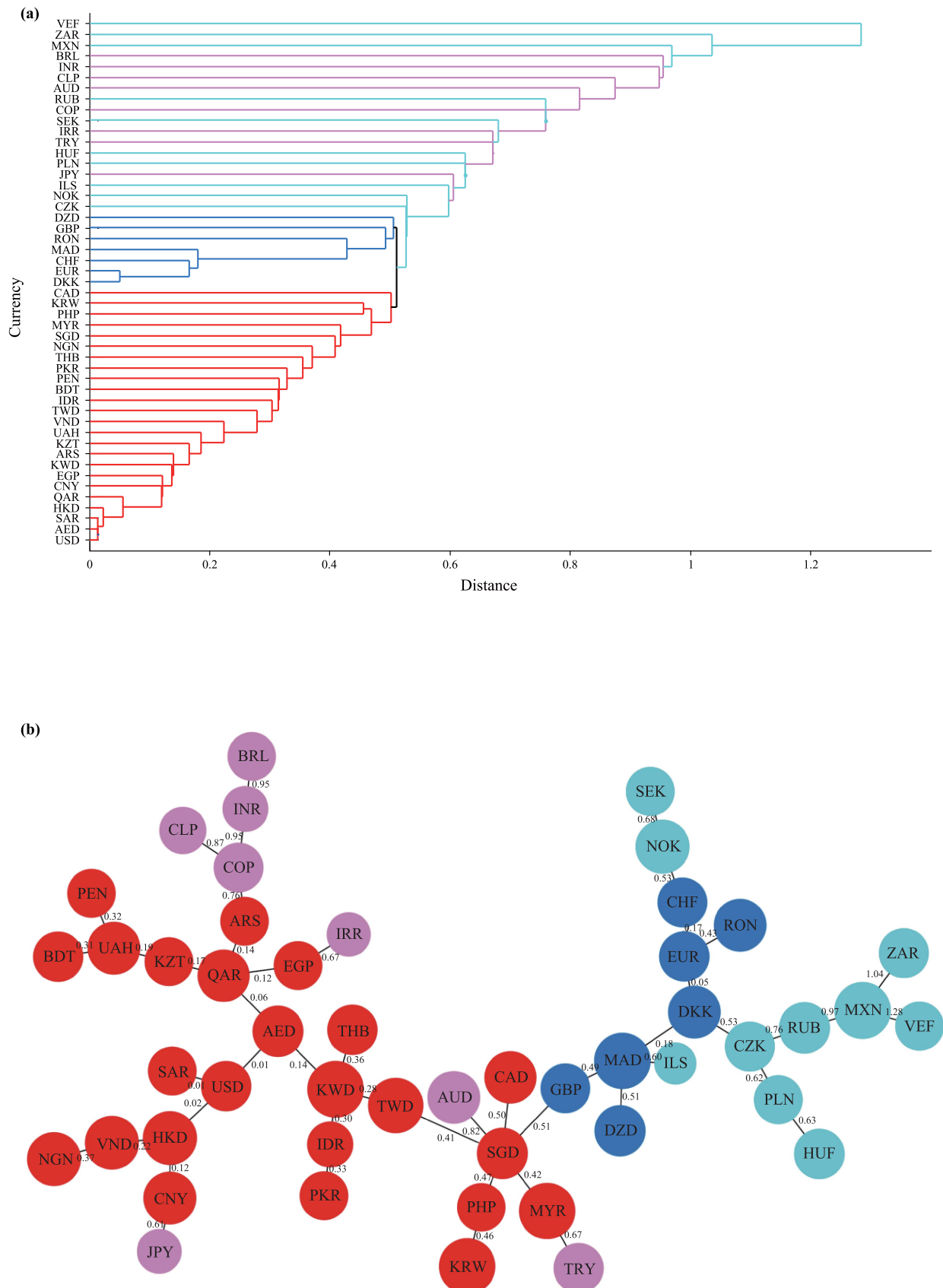
In Fig. 3(a), it can be found that the NZD-based HT includes two clusters, marked as red and blue.

The blue cluster includes typical currencies such as GBP, MAD, DKK, EUR, RON, CHF, DZD, where most of these blue nodes are European, except two African nodes MAD and DZD. The sphere of the blue cluster are labeled as light blue, which includes 6 European currencies (SEK, NOK, CZK, PLN, HUF, RUB), 2 Latin American currencies (VEF, MXN), 1 Asian currency (ILS), and 1 African currency (ZAR). It can be clearly found that the dominant part of this sphere is still European. Therefore the blue cluster and its light-blue sphere form a huge blue group, including 11 of 13 European currencies, 3 of 5 African currencies, 2 of 7 Latin American currencies and 1 of 21 Asian currencies. European currencies form the leading part of this group. In fact, it is not difficult to explain that Morocco, Algeria and Israel belong to the European cluster because they are all Mediterranean. Thus the blue cluster, its sphere of influence and the whole groups are all highly geographical aggregated. Obviously, the Pan-European is their common factor. In the respective part of MST in Fig. 3(b), it is obviously that DKK is the central of the blue group.

Now let us look at the red cluster in Fig. 3(a). There are 24 currencies in this cluster, including all the Asian currencies except ILS, INR, IRR, JPY, 2 of 7 Latin American currencies (ARS, PEN), all 2 North American currencies (CAD, USD), 2 of 5 African currencies

Table 1 Countries/Regions and respective currency symbols.

Continent	Country/Region	Currency Sym	Continent	Country/Region	Currency Sym
Oceania	Australia	AUD	Asia	Japan	JPY
	New Zealand	NZD		India	INR
North America	United States	USD		Korea, Rep.	KRW
	Canada	CAD		Indonesia	IDR
Latin America	Brazil	BRL		Taiwan	TWD
	Mexico	MXN		Thailand	THB
	Venezuela	VEF		Malaysia	MYR
	Argentina	ARS		Hong Kong	HKD
	Chile	CLP		Singapore	SGD
	Peru	PEN		Philippines	PHP
	Colombia	COP		Pakistan	PKR
Europe	Euro group	EUR		Kazakhstan	KZT
	United Kingdom	GBP		Vietnam	VND
	Russian Fed.	RUB		Bangladesh	BDT
	Turkey	TRY		Saudi Arabia	SAR
	Switzerland	CHF		Iran, Islamic Rep.	IRR
	Poland	PLN		United Arab Emirates	AED
	Sweden	SEK		Israel	ILS
	Norway	NOK		Kuwait	KWD
	Denmark	DKK		Qatar	QAR
	Czech Rep.	CZK	Africa	Egypt, Arab Rep.	EGP
	Romania	RON		Algeria	DZD
	Ukraine	UAH		South Africa	ZAR
	Hungary	HUF		Nigeria	NGN
				Morocco	MAD
Asia	Mainland of China	CNY			



(EGP, NGN), and an European currency UAH. The sphere of influence (labeled as pink) of this red cluster contains 8 currencies, including 3 of 7 Latin American currencies (BRL, CLP, COP), 3 Asian currencies (INR, IRR, JPY), 1 European currency (TRY) and 1 Oceania currency (AUD). The red cluster and its pink sphere also form a huge red group, including 20 of 21 Asian currencies except ILS, 5 of 7 Latin American currencies, all the North American and Oceania currencies, 2 of 5 African currencies and 2 European currencies. Again, geographical aggregation appears. The main parts of the red cluster, its sphere and the whole red group all locate around Pacific Ocean, thus they are Asia-Pacific. In the respective part of MST in Fig. 3(b), SGD is the hub in the MST with the highest degree of 6. There are 4 Eastern Asian currencies (KRW, PHP, MYR, TWD, all red) around it, as well as another Northern American currencies CAD (red), and two pink currencies (AUD(Oceania) and TRY(European)). 5 of 6 of these nodes locate around the Pacific Rim, suggesting that SDG is an important node in this region. The edge SGD-GBP also connects two groups, also presents the importance of the SDG in the global FX market.

QAR, KWD has a degree of 4, and AED, USD has a degree of 3. All these 4 nodes form a core in the red group and handle the central traffic tunnel in the group. It should be noticed that, Qatar(QAR), Kuwait(KWD), United Arab Emirates(AED) are all oil countries, as well as Saudi Arabia(SAR). All these 4 Middle-East oil currencies aggregate around USD and form a core, then other countries expand around this core. This phenomenon clearly implies an oil resource aggregation.

One can also find a smaller cluster, i.e., the KRW-PHP cluster, which is composed by two Eastern Asian currencies. This is also an evidence of geographical aggregation.

4.2 The XAU-based FX market network analysis

The above discussions are based on the analysis of the currency-based HCT. As a comparison, we give the XAU-based results of the FX market in 2012 in Fig. 4. In Fig. 4(a), the HT with colored links implies a two-cluster structure of the FX market, which well agrees with the analysis presented in Fig. 3(a). We first observe the structure of the blue cluster in the XAU-based HT. The cluster possesses almost the same currencies with the former one in Fig. 3(a), including GBP, MAD, DKK, EUR, RON, CHF, except DZD. There are also similar currencies in the light-blue sphere, including the same European currencies such as SEK, NOK, CZK, PLN, HUF, RUB, the same Asian currencies ILS, and also a Latin American currencies VEF (without MXN and ZAR). Therefore, the blue group in Fig. 4(a) contains the

same 11 European currencies as that in Fig. 3(a), as well as ILS (Asian), VEF (Latin American), MAD (African). There is no doubt that, this group is the Pan-European cluster. In the respective part of MST in Fig. 4(b), DKK and EUR form a central core in the blue group, which may due to Denmark's EUR-pegging policy.

The red cluster in Fig. 4(a) is totally the same as that given in Fig. 3(a). The pink sphere in Fig. 4(a) contains the same currencies as the one in Fig. 3(a), and 4 additions, including 2 African currencies DZD, ZAR, 1 Latin American currency MXN and 1 Oceania currency NZD. This red group is undoubtedly the Asia-Pacific branch. In the respective part of MST in Fig. 4(b), the SGD has a degree of 5, and take a similar position to that in Fig. 3(b), with the same 4 Eastern Asian Currencies PHP, MYR, TWD, MYR (all in red) around, as well as CAD (red) and TRY (pink), and an addition MXN (pink). This further indicates that SGD is an important node in the Pacific Rim. The edge SGD-GBP still holds the connection between two groups.

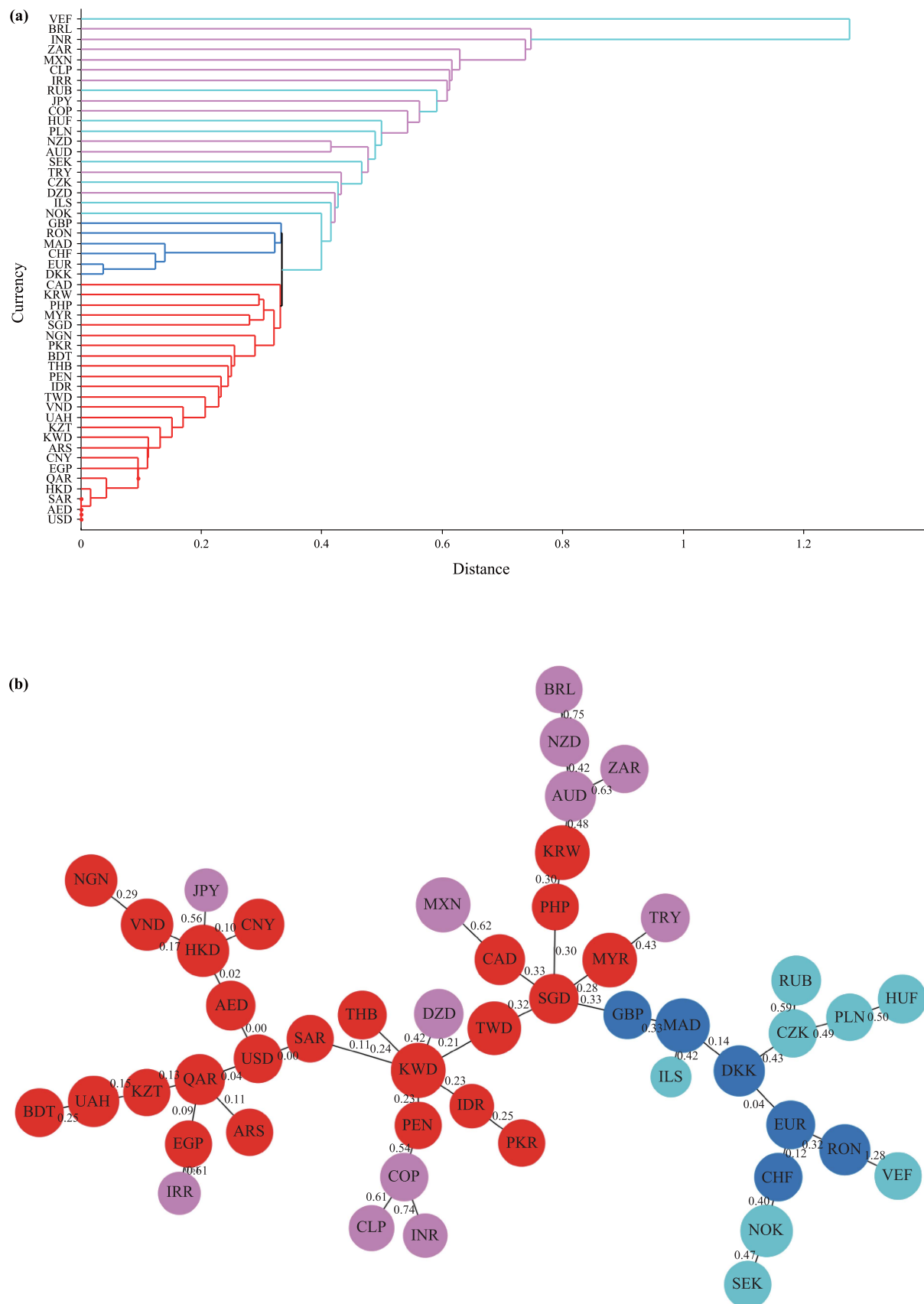
The oil resource aggregation can be more obviously observed in Fig. 4(b). KWD has the highest degree of 6, while SAR, USD, AED, QAR hold the central traffic of the red group and USD is in the middle.

From the XAU-based MST, one can find more mini-clusters. For example, smaller clusters such as NZD-AUD, KRW-PHP, and MYR-SGD can be observed. It is interesting that all these mini-clusters are also aggregated.

5 Conclusions

In this paper, we proposed a hierarchical cluster-tendency method to study the cluster structure of the networks. The method gives a colored hierarchical tree and a colored minimum spanning tree. By distinguishing different colors, one may clearly find the clusters embedded in a complex network of elements. The HCT method is generic and can be well applied to studies of different complex systems.

Based on the HCT analysis, the weekly exchange rates of the 2012 global FX market are studied. For both the NZD-based and XAU-based computations of the correlation coefficient matrices and the distance matrices, we revealed a number of important properties of the clustered structure of the FX market in 2012. First, the global FX market is composed of the Pan-European cluster and the Asia-Pacific cluster [27]. All currencies belong to either one of these two clusters. Moreover, we found a highly geographical aggregation and the oil resource aggregation. Daily exchange rates of the 2012 global FX market are used to examine these conclusions, and we find that



the qualitative results are not changed. The scenario agrees well with the analysis based on other economic data. In addition, the geographical aggregation is observed widely in different financial systems, such as stock market [38–41], foreign trade [42], and the world's automotive industry [43]. We also find that gold could be an acceptable numeraire because the NZD-based results and the XAU-based results are mutually authenticated.

The Foreign Exchange market is huge and complex, and there are still many unsolved issues. The first problem is a more detailed analysis of the FX market by covering more currencies. In the present work we select only 50 from almost 200 currencies based on their national economic performance. It is valuable to study the cluster structure of the FX network by introducing more currencies. It is also an interesting topic to use other economic ranking standards for choosing the currencies as the system under study.

Besides the topological structure of the world FX market, an important issue of the FX market is the dynamical evolution of the FX networks. It has been found that the topological structure of the FX network varies with time, and distinct changes can be found during some important world affairs. It is well expected that the HCT method can be well applied to the cluster dynamics of the FX market network, which is the topic we will further go on.

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